

Upscaling and Downscaling—A Regional View of the Soil–Plant–Atmosphere Continuum

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ABSTRACT

The strength of interaction among soil, plants, and atmosphere depends highly on scale. As the spatial scale of organized soil–plant behavior (e.g., soil drying and/or stomatal closure) increases, so does the influence the land surface has on atmospheric properties and circulations. Counterbalancing this is a system of feedback loops that serve to reduce the sensitivity of surface fluxes to changes in surface conditions. Model upscaling involves capturing land–atmosphere feedbacks and effects of land surface heterogeneity on surface fluxes and atmospheric boundary-layer dynamics that become operative at progressively larger spatial scales. Conversely, by downscaling, we learn how to appropriately parameterize subgrid-scale phenomena within large-scale modeling frameworks. This paper discusses some of the major challenges faced today in properly describing system behavior at regional spatial scales. We focus on a suite of simple biophysical models, tied closely to remote sensing, that work synergistically from canopy to mesoscales. This suite includes a diagnostic regional-scale model used for routine mapping of flux and moisture conditions across the United States at 10-km resolution. A related approach disaggregates regional flux estimates to local scales (10^0 – 10^2 m) for comparison with ground-based measurements or for use in site-specific agricultural or resource management applications. Coupled with turbulence- and mesoscale atmospheric models, the core land surface representation provides means for assimilating remote sensing data into large-eddy simulations and improving short-range weather forecasts. This multiscale modeling framework is being utilized in a concerted research effort aimed at identifying scale-relevant land–atmosphere feedbacks and representing surface heterogeneity efficiently and robustly in regional modeling schemes.

FOR ENVIRONMENTAL BIOPHYSICISTS, upscaling within the soil–plant–atmosphere continuum involves a cascade or transport of knowledge between regimes of increasing spatial scale. How do landscapes behave differently than isolated leaves or plants, for example, and how do these differences in behavior affect how we represent them in biophysical models? This is an important question because we collect most of our detailed information about plant behavior at the leaf level while many of the practical modeling applications are at the landscape or larger scales. Models constructed to function at a given scale can often serve to inform models at other scales but are not generally directly transportable between scales.

A current challenge in biophysical upscaling lies in dealing with model subpixel heterogeneity. As model grid scale increases, so does the probability that a single

pixel will contain several vastly different surfaces: bare soil, standing water, vegetation, parking lots, etc. How does one assign appropriate values to bulk model parameters associated with strongly heterogeneous pixels? The issue becomes more complex when one considers that it is not only the census of constituent surfaces within a model pixel, but also the specific spatial arrangement of those surfaces that is important—patchworks of different scale and configuration can induce edge effects, advection, and circulation that may be significant.

Conversely, we need to also consider issues in downscaling from regional models, which are generally less complex, to the landscape and field scales that are most useful in hydrologic, ecological, biological, and agricultural applications (Jarvis, 1993). In fact, a modeling framework that can operate in both upscaling and downscaling modes would provide the necessary capabilities for addressing general scaling issues related to soil–plant–atmosphere dynamics.

This paper will focus on a suite of models that function synergistically over a large range in spatial scales. These models emphasize both upscaling and downscaling approaches using information provided by visible and thermal infrared remote sensing data, acquired at spatial resolutions from 1 m to 10 km.

FROM LEAF TO LANDSCAPE

In well-ventilated growth chamber experiments, leaves tend to behave like test particles, with leaf-level fluxes responding passively to external environmental forcings such as wind speed, radiation, temperature, humidity, C concentration, and soil water content. However, when many leaves are assembled into the form of a plant or a canopy of plants and allowed to function in a natural environment, they will begin to actively modify the forcing fields in their immediate vicinity, and these modifications can feed back significantly on the bulk behavior of the leaf ensemble itself. When these feedback systems are not considered in upscaled models, canopy-level states, fluxes, and sensitivity to environmental changes (such as elevated ambient CO_2 levels) can be misrepresented (Jacobs and DeBruin, 1992, 1997; Carlson and Bunce, 1996; Bunce et al., 1997; Jones, 1998; Raupach, 1998; Wilson et al., 1999; Gottschalck et al., 2001).

In two related papers (Jarvis and McNaughton, 1986; McNaughton and Jarvis, 1991), Jarvis and McNaughton convey a qualitative understanding of how feedback systems work on different spatial scales. They address

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Abbreviations: ABL, atmospheric boundary layer; APAR, absorbed photosynthetically active radiation; ET, evapotranspiration; LES, large-eddy simulation; LUE, light use efficiency.

Table 1. Scale dependence of feedback.

Scale	Scale size/grid resolution	Control surface	Feedback
Leaf Plant Canopy	A few cm cm–m 100 m–km	Leaf boundary layer Compound leaf/cluster boundary layer Surface layer	Decoupling by leaf boundary-layer resistance Decoupling by leaf cluster boundary-layer resistance Decoupling by bulk canopy boundary-layer and aerodynamic resistance
Landscape Mesoscale	Several km 10–100 km	ABL† Mid-troposphere	ABL growth/entrainment; Large eddy circulations Organized mesoscale circulations

† ABL, atmospheric boundary layer.

a long-standing dispute between plant physiologists and atmospheric scientists as to whether stomatal aperture or radiation receipt is more important in controlling transpiration rates. The first paper looks at feedbacks among stomatal conductance, transpiration, and humidity conditions. The second incorporates radiative coupling—feedback between leaf temperature and net radiation. Subsequent papers by other researchers (e.g., Raupach, 1998) have examined the coupling between surface temperature and atmospheric stability and other feedback effects. These papers demonstrate that the spatial scale over which plant behavior is organized and uniform determines the extent to which environmental self-modification occurs and the strength that these feedback cycles can attain. Scale of application also influences the level of detail that needs to be included in biophysical models and where the model boundary conditions should be defined (Table 1).

Leaf Scale

Jarvis and McNaughton (1986) note that a single stoma opening and closing in isolation will have negligible effect on the microclimate at the leaf surface. However, organized closure in some modest percentage of the stomatal population across the leaf surface—triggered by changes in light intensity, CO₂ concentration, leaf water loss, or environmental stress (Collatz et al., 1991; Collatz et al., 1992)—can significantly modify the temperature and humidity within the leaf boundary layer (e.g., Ball et al., 1986). External boundary conditions for leaf-scale models must therefore be defined outside the boundary layer where they are more or less independent of system fluxes in this context.

Inside the boundary layer, a negative feedback cycle serves to decrease the sensitivity of the leaf-scale transpiration flux to small changes in stomatal resistance. An incremental increase in the bulk stomatal resistance will decrease transpiration and reduce the humidity at the leaf surface. In turn, this increases the saturation deficit of this boundary layer air with respect to the substomatal cavities, thereby enhancing transpiration and partially offsetting the original reduction. A fractional change in stomatal resistance does not yield an equivalent fractional change in transpiration, so stomatal control is not absolute at the leaf scale.

Jarvis and McNaughton (1986) point out that the strength of this feedback cycle depends on how decoupled the leaf surface is from the external atmosphere. As the leaf boundary layer resistance becomes large compared with the stomatal resistance, water vapor is more effectively trapped near the leaf surface, and tran-

spiration rates become less sensitive to incremental changes in stomatal resistance. However, large, abrupt changes in stomatal resistance, due to moisture or heat stress for example, can cause this feedback cycle to break down.

Plant Scale

On the plant scale, leaves often grow in clusters with overlapping boundary layers, so the modeling control surface in this case must at least encompass the full compound leaf or cluster. The effective boundary-layer resistance (decoupling) for the cluster will be greater than that of an individual leaf, so stomatal control of transpiration is further reduced at the plant scale (Jarvis and McNaughton, 1986).

Canopy Scale

Uniform fluxes from an extensive array of plants can influence the microclimate both within and above the canopy. To ensure independent boundary conditions, the reference height at this scale of modeling should lie above the surface layer influenced by the canopy, at the base of the well-mixed atmospheric boundary layer (ABL), ~50 to 100 m above the surface. The plants are decoupled from the free atmosphere by both the bulk leaf boundary-layer resistance and the aerodynamic resistance through the surface layer; so canopy-level transpiration is even less sensitive to fractional changes in stomatal conductance than on the single plant scale and more dependent on net radiation receipt (Jarvis and McNaughton, 1986; McNaughton and Jarvis, 1991). Aerodynamically rough canopies (such as sparse forests) will in general be better coupled with the atmosphere than will smooth, dense canopies (such as pastures and grasslands) and will therefore retain tighter physiological control over transpiration rates (e.g., Jarvis and McNaughton, 1986; Grantz and Meinzer, 1990; Magnani et al., 1998; Wullschlegel et al., 2000).

Landscape Scale

At landscape scales, the patchiness of vegetative behavior becomes increasingly important. Large patches of uniform surface behavior can affect the state of the atmosphere all the way up to and beyond the top of the convective ABL—a few kilometers, vertically. Even at this scale, there are feedback cycles that tend to stabilize latent heat flux in the event of small changes in canopy conductance. When sensible heating is increased due to widespread stomatal closure, the growth of the ABL is accelerated, and hotter, drier air is entrained from above

the capping inversion. The saturation deficit in the ABL increases, and latent heating is enhanced. Especially for surfaces with low canopy resistance, such as well-watered crops, evapotranspiration (ET) becomes increasingly radiation-driven at larger scales (Jarvis and McNaughton, 1986; McNaughton and Jarvis, 1991; Albertson et al., 2001a).

The power spectrum of atmospheric turbulence peaks at the kilometer scale—around the scale height of the ABL. At these scales, transport of scalars by large, turbulent eddies can become important, generating counter-gradient fluxes that present challenges to traditional gradient transport theory.

Mesoscale

At larger scales, complexity in modeling increasingly shifts toward the atmospheric end of the soil–plant–atmosphere continuum. Strong horizontal gradients in surface sensible and latent heating associated with surface inhomogeneities can induce organized mesoscale circulations, like sea breezes, that can extend beyond the ABL and into the midtroposphere (Mahfouf et al., 1987; Avissar and Pielke, 1989; Pinty et al., 1989; Pielke et al., 1991; Segal and Arritt, 1992; Avissar and Liu, 1996). These circulations can influence cloud and precipitation patterns (Anthes, 1984; Chen and Avissar, 1994; Avissar and Liu, 1996; Freedman et al., 2001), which may feed back measurably on upwelling surface fluxes. One of the major fronts of research in upscaling today is in identifying characteristic scales and strengths of patchiness leading to turbulent and mesoscale circulations.

Implications of Feedback to Modeling

Based on these considerations, Jarvis and McNaughton (Jarvis and McNaughton, 1986; McNaughton and Jarvis, 1991; Jarvis, 1993, 1995) draw two important conclusions regarding the implications of system feedback and scale on biophysical modeling.

First, because stomatal control over surface fluxes tends to weaken with increasing patch size, vegetation models designed for larger scales can often afford to be less complex than leaf- or plant-scale models (see also Avissar, 1993). Excessive model complexity may result in a large number of tunable parameters that cannot be specified with acceptable accuracy over regional scales. It can also lead to nonphysical or unstable solutions if the model is not well tied to observations made at the scale of application. Introducing scale-appropriate empirical constraints can keep the model from wandering into strange corners of solution space. A caveat is that the model can then be used prudently only under the conditions in which the constraints were developed.

Second, model boundaries are ideally defined such that they contain the full system of feedbacks effective at the scale of operation. This ensures that the boundary conditions are essentially independent of the system itself. Canopy simulation studies using real weather data should address the extent to which feedback from the canopy itself has already been integrated into the ob-

served wind speed, temperature, dew point, and precipitation rates. Brutsaert (1984) reviews several analytical and numerical models that describe the adjustment of internal boundary layers to step changes in surface roughness, wetness, and humidity, which can be useful in determining case-specific fetch and measurement height requirements for meteorological inputs to vegetation models (see also, Klaassen, 1992).

CURRENT ISSUES IN SCALING

The simplest (yet most improbable) case of modeling fluxes from homogeneous multikilometer scale surfaces has been well studied. Many of the current challenges in regional flux modeling lie in dealing with subpixel heterogeneity due, for example, to spatial variations in canopy resistance, vegetation cover and type, topography, cloud cover, and soil moisture.

First, what are the best ways to validate predictions of regional-scale fluxes? Observations from ground-based flux towers, sampling spatial footprints on the order of hundreds of meters, will often not be representative of fluxes on the kilometer scale (see, e.g., Holwill and Stewart, 1992; Divakarla, 1997). An aircraft can sample a flux footprint of several kilometers (Schuepp et al., 1992), but such flights are logistically complicated and expensive, and it is difficult to obtain large data sets over wide variety of surface conditions to facilitate extensive model validation.

Next, how is it possible to assign a single value to a property like leaf area index or surface roughness associated with a 10- to 100-km model grid cell? Radiative and turbulent fluxes are typically nonlinearly related to these types of critical input parameters, so using simple linear areal averages can introduce large errors into regional-scale flux calculations (Avissar, 1992; Bonan et al., 1993; Li and Avissar, 1994; Kustas and Norman, 2000a). Different parameter-averaging schemes have been devised to preserve areal averages of different surface states or fluxes (Lhomme, 1992; Lhomme et al., 1994; McNaughton, 1994; Raupach and Finnigan, 1995; Chebouni et al., 1995; Chebouni et al., 2000), but there will generally be a compromise. For example, McNaughton (1994) showed that an effective canopy resistance can be generated that will preserve scaled estimates of ET or surface temperature but not both.

A related question then is what scales and patterns of inhomogeneity will tend to corrupt regional scale fluxes computed from areally determined effective parameters? Shuttleworth (1988) and Raupach (1991) identify a scale threshold (≈ 10 km) distinguishing *disorganized* or microscale surface heterogeneity from *organized* mesoscale heterogeneity. Above this threshold, surface patterns such as widespread stomatal closure can begin to have a significant influence on mean atmospheric properties and dynamics. Different parameter aggregation rules may need to be developed for organized and disorganized landscapes (Shuttleworth, 1988; Raupach, 1991). Furthermore, scales and amplitudes of heterogeneity must be identified that cause surface-induced variations in atmospheric state, turbulence, and

large-scale circulation patterns to feed back on the surface fluxes themselves.

Finally, because upscaling by definition requires characterization of land surface conditions at large spatial scales, it will be useful to exploit available remote sensing information as fully and creatively as possible in regional-scale modeling (Bastiaansen et al., 1998; Avisar, 1998). The thermal and microwave wavebands have been somewhat neglected compared with the enormous effort that has been given to developing visible/near-infrared-based data products, but the information content regarding surface state provided in the longer wavelengths is becoming increasingly evident (e.g., Moran et al., 1994; Gillies and Carlson, 1995; Anderson et al., 1997; Kustas et al., 1998; Li and Islam, 1999; Boni et al., 2001; Moran, 2003). It may be that the biggest strides in remote sensing data assimilation in the next decade will be made on the longer wavelength end of the electromagnetic spectrum.

Issues in upscaling and downscaling soil-plant-atmosphere models are currently being addressed in three broad foci of research, including the study of flux aggregation and disaggregation, the simulation of large-scale turbulent eddies and mesoscale circulations, and the examination of means for assimilating disparate forms of observational data into existing models. In the following, we present a case study of modeling applications in these three fields of research and demonstrate how

they are being used to fill current gaps in our understanding of scaling.

A HEIRARCHY OF MODELS

A series of papers (Norman et al., 1995b, 2003; Anderson et al., 1997, 2000; Mecikalski et al., 1999) published over the last decade outlines a suite of simple biophysical models, tied closely to remote sensing, that work synergistically from canopy to mesoscales through modification of model boundary conditions (Fig. 1–2). These models are intended for diverse, routine applications and therefore attempt to balance the competing demands of generality and simplicity. They have been designed to accommodate varying surface conditions while remaining computationally inexpensive and requiring only a tractable array of surface parameters. This multi-scale modeling framework is being utilized in a concerted research effort aimed at identifying scale-relevant land-atmosphere feedbacks and representing surface heterogeneity efficiently and robustly in coupled models.

At the core of each of these models is a two-layer or two-source (plant + soil) land surface representation coupling conditions inside the canopy to fluxes from the soil, plants, and atmosphere.

ALEX

A diagram describing the *forward*, or prognostic, canopy-scale model of atmosphere-land exchange (ALEX)

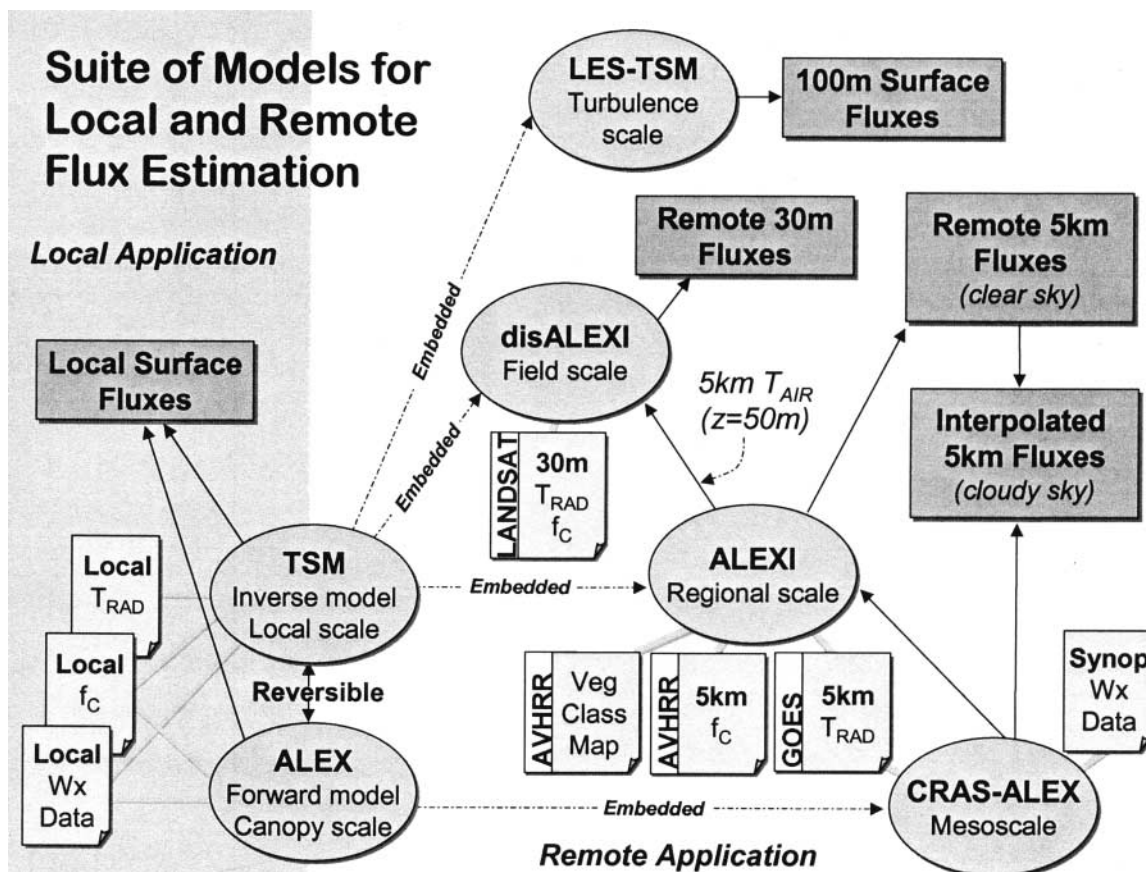


Fig. 1. The genealogy of the ALEX multiscale modeling suite.

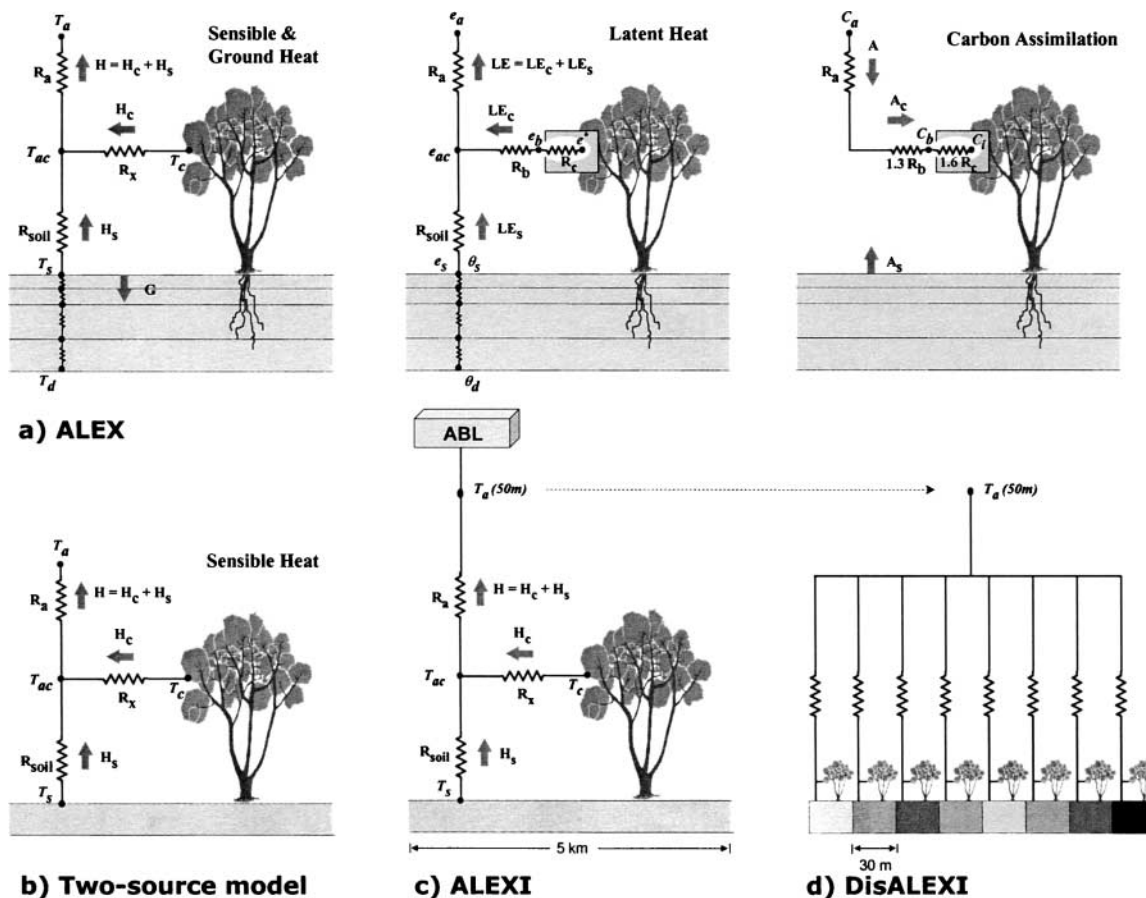


Fig. 2. Schematic descriptions of (a) the ALEX model of sensible and latent heating and C assimilation fluxes, (b) the remote sensing two-source model (TSM), (c) the regional-scale ALEXI model, and (d) disaggregated ALEXI (DisALEXI) model. ABL, atmospheric boundary layer.

of C, water, and heat is shown in Fig. 2a. The unique feature of the ALEX model is its treatment of canopy resistance, which exploits the conservative nature of transpiration and photosynthetic processes occurring on the stand level. Instead of using a scaled numerical solution to several leaf-level photosynthetic equations (e.g., Sellers et al., 1996), canopy resistance in ALEX is computed using a second-order analytical expression (Anderson et al., 2000) parameterized in terms of the canopy light use efficiency (LUE) and the absorbed photosynthetically active radiation (APAR). This analytical solution agrees well with numerical solutions (Anderson et al., 2000) but is computationally more efficient and stable and uses fewer tunable parameters. And since it is tied to a stand-level measurement—the canopy LUE—the solutions are constrained to lie within the realms of observation.

Light use efficiency has been measured for many different plant species and has been found to be fairly conservative within vegetation classes when the plants are unstressed and when disparities in measurement technique are accounted for (Monteith, 1977; Field, 1991; Arkebauer et al., 1994; Goetz and Prince, 1998; Gower et al., 1999; Anderson et al., 2000). Because assimilation scaling effects are implicitly incorporated into its measurement on the stand level, LUE can provide a valuable constraint to canopy resistance modeling. Models constrained by LUE (e.g., Potter et al.,

1993; Ruimy et al., 1994; Prince and Goward, 1995) are particularly well suited to application over large geographical regions because they are founded on a quantity that can be derived with reasonable accuracy from remote sensing: APAR (e.g., Kumar and Monteith, 1981; Daughtry et al., 1983; Steinmetz et al., 1990; Myneni et al., 1995a, 1995b). Furthermore, as discussed above, system feedbacks at these larger scales cause ET fluxes to be increasingly radiation-driven and less sensitive to physiological control by surface vegetation.

The effective LUE diagnosed by the analytical model is typically near the nominal stand-level measurement (an input parameter, indexed by vegetation class) but responds to varying environmental conditions in humidity, temperature, CO_2 concentration, and light quality. Stomatal closure in response to water stress and extreme temperatures is simulated through incorporation of empirical stress functions (Norman, 1979; Campbell and Norman, 1998). Hourly and daily estimates of ET and C assimilation from the ALEX model agree well (to within 15%) with micrometeorological measurements made in six different vegetative stands (see Fig. 3). This accuracy is comparable to the 10 to 20% instrumental variation that Twine (1998) identified among micrometeorological flux measurements made during the Southern Great Plains 1997 field experiment (SGP97; Jackson et al., 1999). Given its robustness and computational efficiency, the ALEX model has been utilized in several

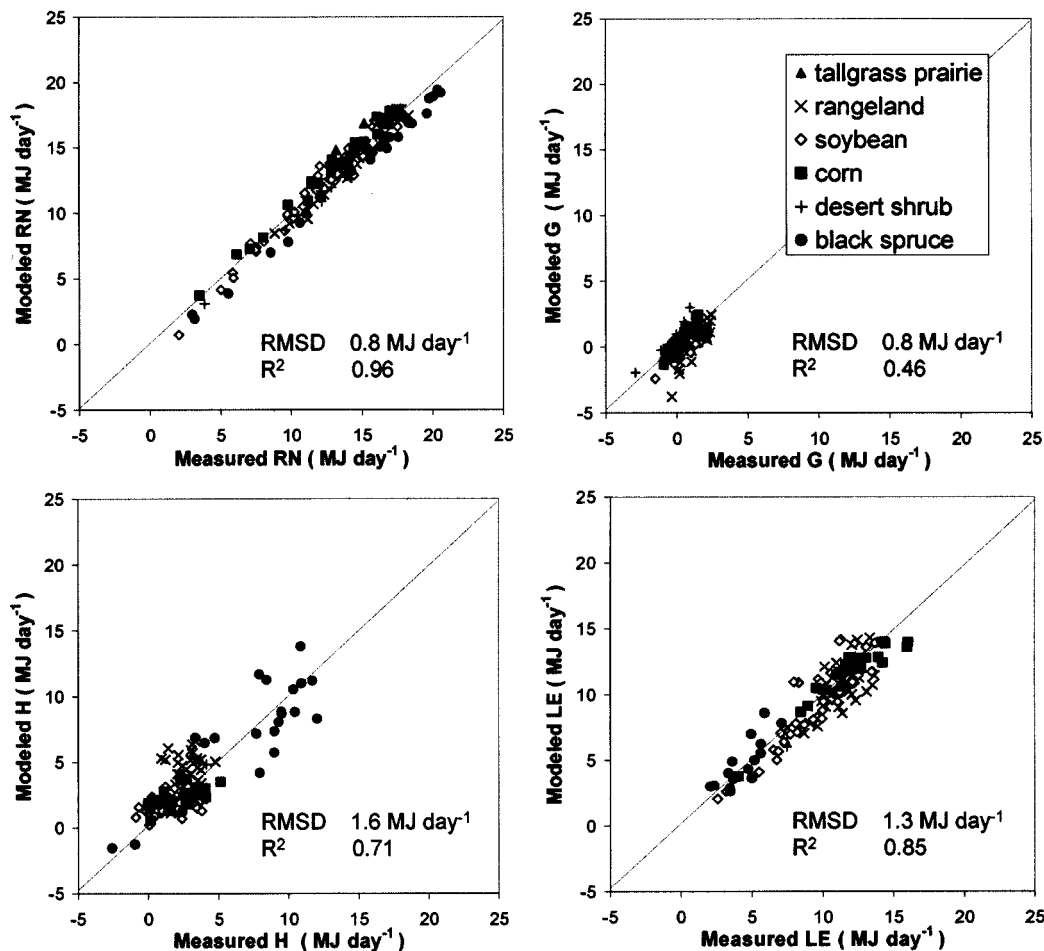


Fig. 3. Comparison of daily integrated measurements of net radiation (RN), soil heat flux (G), sensible heat (H), and latent heat (LE) made in six vegetative stands with estimates generated by the ALEX model. The root mean square difference (RMSD) between measurements and model estimates for all fluxes combined is 0.9 MJ day^{-1} (15% of the mean observed flux), with a coefficient of determination (R^2) of 0.97 (Anderson et al., 2000).

operational agricultural forecasting products (Diak et al., 1998; Anderson et al., 2001).

The ALEX model was developed in comparison with a significantly more detailed soil-plant-atmosphere model, Cupid (Norman, 1979; Norman and Campbell, 1983; Norman and Polley, 1989; Norman and Arkebauer, 1991). Cupid models the leaf-level responses of photosynthesis (using the formalism of Collatz et al., 1991, 1992 for C_3 and C_4 species, respectively) and energy balance to environmental forcings within multiple leaf classes, stratified by leaf angle and depth within the canopy. Canopy-level responses are simulated by numerical integration over all leaf classes. Anderson et al. (2000) found that the simple analytical canopy resistance model described here performed as well and often better than the more detailed, process-based Cupid model in predicting energy partitioning between soil and vegetation.

While the LUE approach to modeling canopy resistance significantly reduces the number of requisite model inputs and parameters, ALEX still requires specification of soil thermal and hydraulic properties, as well as boundary conditions in temperature and humidity above the canopy. Given these requirements, ALEX is

most appropriately run at local scales where these inputs can be specified through in situ measurement.

Two-Source Model

Over larger spatial scales, detailed soil profile information will not generally be available with adequate spatial coverage. Norman et al. (1995b) developed a remote sensing version of the ALEX model in which lower boundary conditions in surface temperature are prescribed by thermal infrared observations rather than soil modeling (Fig. 2b). This inverted model is somewhat less constrained by the need for local measurements and is therefore better suited for regional-scale applications. Inversion has been facilitated by the simplicity of the core model, which can be adapted with relative ease to assimilate new forms of input data, including microwave observations (Kustas et al., 1998).

The two-source remote sensing model (TSM) partitions the composite thermal signature of a heterogeneous scene into soil and canopy contributions, given an estimate of the fractional vegetation cover within the scene. The two-source representation is a major improvement over previous single-layer thermal mod-

els, which required site-specific adjustments to compensate for differences in aerodynamic coupling among the soil, canopy, and atmosphere (Kustas et al., 1989; Hall et al., 1992; Stewart et al., 1994; Kubota and Sugita, 1994). It also provides a means for accommodating the dependence of apparent surface temperature on view angle, caused by the variable obscuration of the underlying bare soil when a canopy is viewed off-nadir (Vining and Blad, 1992; Norman et al., 1995b). Modifications to model parameterizations of radiation and wind extinction for clumped heterogeneous vegetation conditions continue to improve the robustness of the two-source algorithm (Kustas and Norman, 1999a, 1999b, 2000b).

In principle, the TSM can be applied at a wide range in spatial scales; however, Kustas and Norman (2000a) show that strong subpixel heterogeneity in surface properties, such as vegetation cover and soil moisture, can serve to corrupt flux estimates based on pixel-averaged model input parameters. Particularly problematic are situations where 20 to 80% of the pixel is comprised of dry, nearly bare soil while the remaining area is highly vegetated and well watered (as is the case in many agricultural settings). For such surfaces, assuming a pixel-averaged vegetation cover resulted in significant ($>100 \text{ W m}^{-2}$) underestimation of latent heating (note, however, that this study did not consider surface-atmosphere feedbacks, which are likely to reduce the effects of subpixel heterogeneity; see below). Pixel-average cover estimates do not properly weight the effects of the (typically hotter) bare soil subcomponent, which contributes more strongly to the pixel's surface temperature than to its sensible heat flux due to the insulating effects of the soil surface boundary layer. Subpixel cover heterogeneity has been addressed by modeling *homogeneous* subpatches directly or statistically (e.g., Avissar and Pielke, 1989) or by applying a pixel-scale vegetation clumping factor, which yields an *effective* vegetation cover that more realistically preserves the pixel-average fluxes (e.g., Kustas and Norman, 1999a). In either case, subpixel information on vegetation cover must be available, preferably at the typical scale of the contrasting surface type.

While lower boundary conditions are supplied through thermal remote sensing data, the TSM still requires specification of above-canopy temperature conditions, which are not independent of surface fluxes at the landscape scale. Shelter-level atmospheric properties can be strongly coupled to local surface conditions, so model boundary conditions for remote applications generally cannot be interpolated with adequate accuracy from synoptic weather network observations, with a typical spacing of 100 km. Just a 1°C error in the assumed surface-to-air temperature difference can translate into errors in predicted sensible heating of up to 100 W m^{-2} , depending on wind speed and surface roughness (Norman et al., 1995a).

ALEXI

On regional scales, model boundaries must be extended to include the ABL to capture relevant land-atmosphere feedback; above-canopy conditions can then be simulated such that they are consistent with the

modeled surface fluxes. For the purpose of routine (i.e., daily) mapping of surface fluxes over regional scales, the two-source model has been coupled with the simple slab ABL model of McNaughton and Spriggs (1986), forming the Atmosphere–Land Exchange Inverse model, or ALEXI (Anderson et al., 1997; Mecikalski et al., 1999; Fig. 2c). ALEXI is operationally used to estimate fluxes at 10-km resolution over the continental USA on a daily basis (Mecikalski et al., 1999) and at 5-km resolution over smaller subdomains associated with intensive field experiments.

In ALEXI, the lower boundary conditions for the two-source model are provided by thermal infrared observations taken at two times during the morning hours from a geostationary platform such as the Geostationary Operational Environmental Satellite (GOES). The slab model then relates the rise in air temperature above the canopy during this interval and the growth of the ABL to the time-integrated influx of sensible heating from the surface. Use of time-differential measurements of surface radiometric temperature reduces model sensitivity to errors in absolute temperature due to sensor calibration and surface emissivity corrections. Importantly, the air temperature in the surface layer is not defined as a boundary condition—it is evaluated by the model at the TSM–ABL interface and responds to feedback from both the surface fluxes and the atmospheric profile. The upper model boundary in ALEXI is moved to above the well-mixed ABL where conditions are more uniform at the 5- to 10-km scale.

Primary remote sensing inputs to ALEXI include the morning time rate of change in surface radiometric temperature, downwelling solar and longwave radiation (to compute net radiation), and fractional vegetation cover. A land cover classification map derived from multispectral satellite data is used in conjunction with the cover-fraction map to assign class-dependent surface properties, such as surface roughness, albedo, and emissivity. Ancillary surface and atmospheric data required include an estimate of the wind speed field at 50 m and an analysis of early-morning synoptic radiosoundings of temperature (see Mecikalski et al., 1999).

One potential application of the ALEXI model is in mapping regional surface moisture indices and vegetation stress. Model estimates of soil and canopy latent heating can be compared with potential rates based on radiation load, atmospheric demand, and vegetation cover and used as indicators of available water content in the soil surface ($\approx 0\text{--}5 \text{ cm}$) and root zone ($\approx 5\text{--}200 \text{ cm}$), respectively (e.g., Campbell and Norman, 1998). Thermal methods of stress detection are particularly valuable in that they can provide early warning of impending crop failure (Moran, 2003)—the effects of stress on transpiration and therefore canopy temperature are detectable before actual physiological damage occurs, and evidence appears in visible/near-infrared indices. In ALEXI, a morning surface temperature change larger than expected for a given vegetation cover fraction is taken as indication that transpiration has been throttled back due to stress-induced stomatal closure.

Figure 4a shows a six-day composite of potential system (soil + canopy) ET ratio (actual ET/potential ET)

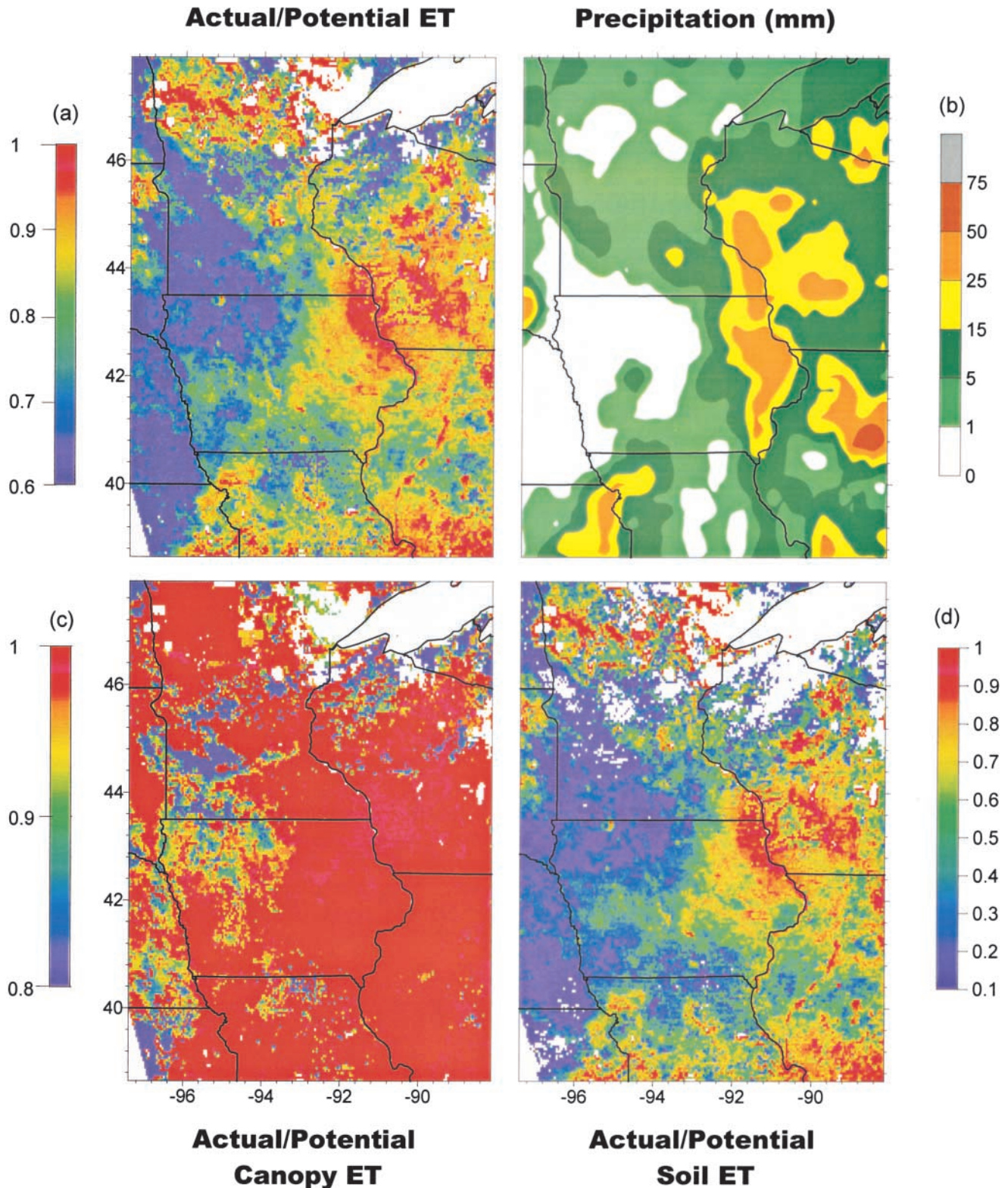


Fig. 4. (a) Six-day composite of system (soil + canopy) potential evapotranspiration (ET) ratio estimates from the ALEXI model at 5-km resolution, ending 1 July 2002. The nominal time associated with this image is 1.5 h before local noon, the time of the second GOES image used to compute surface radiometric temperature change. (b) Six-day accumulated precipitation, based on the National Centers for Environmental Prediction (NCEP) daily precipitation analysis product. (c) Canopy potential ET ratio. (d) Soil potential ET ratio.

predicted by the ALEXI model over a portion of the Midwest USA at 5-km resolution. For comparison, Fig. 4b shows a six-day accumulation of precipitation,

generated from the National Centers for Environmental Prediction (NCEP) Climate Prediction Center daily precipitation analysis product. In general, there is good

qualitative agreement between these two fields. The model has captured the effects of an extended dry spell that occurred in northwest Iowa, southwest Minnesota, and eastern Nebraska where the potential ET ratio is significantly reduced. A series of rainfall events along the Iowa–Wisconsin border, central Wisconsin, and in Illinois have kept ET at near potential rates in these areas. Maps of canopy and soil potential ET ratio in Fig. 4c and 4d indicate that while the soil surface layer has dried substantially in many parts of the domain, canopy transpiration has been curtailed only where the extended dry down has occurred. This behavior is expected as plants have the ability to mine water from deep in the soil root zone.

Note that no information regarding antecedent precipitation or moisture storage capacity was required to

generate these moisture indices—the surface moisture status is deduced primarily from a radiometric temperature change signal. Therefore, ALEXI can provide independent information for updating soil moisture variables in more complex regional models.

Validation of the ALEXI algorithm has been performed using local measurements of radiometric temperature made with ground-based infrared thermometers, which sample an area on the order of tens of meters. With local inputs, ALEXI flux predictions agree well with tower measurements made over canopies of a variety of C_3 and C_4 plant species (Fig. 5; see also Anderson et al., 1997). In practice, however, ALEXI is more suitably applied to satellite-based thermal data acquired at the 5- to 10-km scale—the scale at which atmospheric forcing by organized land surface behavior becomes

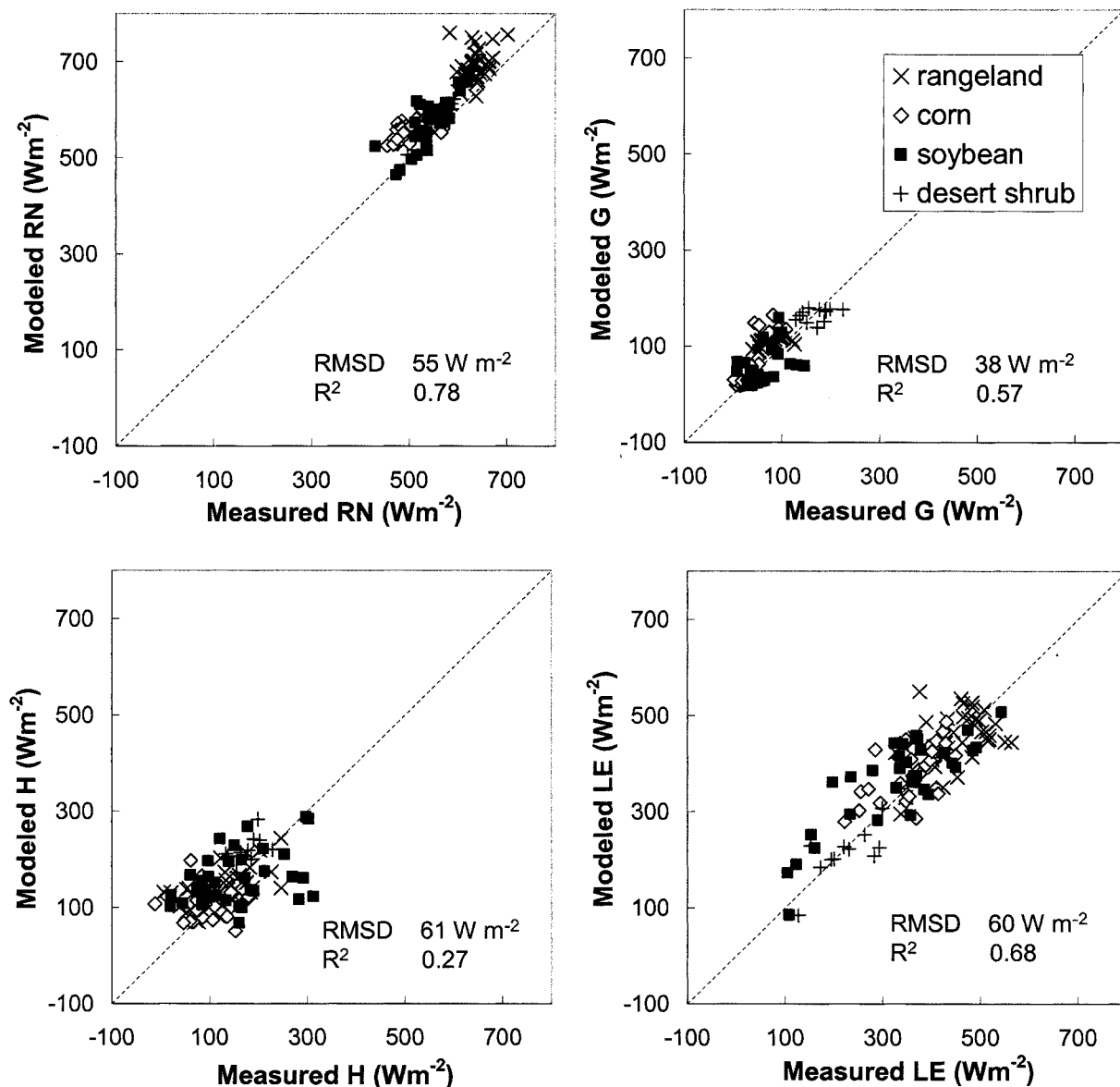


Fig. 5. Comparison of instantaneous measurements (1.5 h before local noon) of net radiation (RN), soil heat flux (G), sensible heat (H), and latent heat (LE) made in four vegetative stands with estimates generated by the ALEXI model using local, ground-based inputs. The root mean square difference (RMSD) between measurements and model estimates for all flux components is $54 W m^{-2}$ (19% of the mean observed flux), with a coefficient of determination (R^2) of 0.95.

effective. Flux predictions at these scales are inherently difficult to validate; for direct comparison with flux tower measurements, which typically sample a footprint on the order of hundreds of meters, the regional-scale model predictions need to be spatially disaggregated.

DisALEXI

Flux disaggregation (or downscaling) requires that important forcing variables be identified that can be determined reliably at the target scale. The Disaggregated ALEXI (DisALEXI) algorithm (Norman et al., 2003) uses high-resolution surface temperature and vegetation cover information acquired by aircraft- or satellite-borne instruments such as the Land Remote Sensing Satellite Enhanced Thematic Mapper Plus (Landsat ETM+), the Advanced Space-Borne Thermal Emission Reflectance Radiometer (ASTER), or the Moderate-Resolution Imaging Spectroradiometer (MODIS).

DisALEXI is a two-step process (Fig. 2d). First ALEXI is executed at a resolution of 5 km to diagnose an above-canopy air temperature that is consistent with the cover fraction and temperature change associated with a 5-km patch of landscape and with the overlying boundary-layer dynamics. The reference level of this interface air temperature must be high enough that the effects of surface heterogeneity are small and conditions are relatively uniform over a 5- to 10-km area. Wieringa (1986) defines such a reference as “the blending height,” which is typically on the order of 50 m above ground level (Raupach and Finnigan, 1995).

In Step 2, the two-source model is applied to high-resolution cover and temperature data, holding the air temperature at the blending height constant over the entire GOES pixel at the ALEXI-derived value. In this

hybrid mode, the atmospheric component of ALEXI is used at the large scales it is best suited for while the surface component can be applied at much finer scales. High-resolution flux estimates from the fetch influencing conditions at the height of the flux sensor can then be reaggregated through a weighted footprint analysis (Schuepp et al., 1990; Horst and Weil, 1992; Schmid, 1994) and compared with tower or aircraft flux measurements.

Figure 6a shows a map of surface radiometric temperature at 30-m resolution made with the Thermal Infrared Multispectral Scanner (TIMS; Palluconi and Meeks, 1985), which was flown by aircraft during SGP97 over a study area near El Reno, OK (French et al., 2000). A map of disaggregated latent heating estimates generated from these high-resolution surface temperature data is shown in Fig. 6b (from Norman et al., 2003). The last significant rainfall occurred 4 d prior; thus, fields of bare soil (harvested winter wheat) are hot and exhibit low evaporation rates (black in Fig. 6b). Densely vegetated stands in riparian zones around a stream network crossing the modeling domain remain cool and with sufficient water to maintain near-potential transpiration rates (white in Fig. 6a). The 30-m latent heat flux estimates, reaggregated using the footprint analysis technique of Schuepp et al. (1990), compare well with flux measurements made at four eddy correlation towers within the study area, situated in pasture sites of varying leaf area index and in a site over bare soil (see Fig. 7; tower locations are demarcated in Fig. 6a). The level of agreement apparent in Fig. 7 gives us some confidence that the 5-km aggregated flux estimates from ALEXI are also reasonable in this case.

The DisALEXI disaggregation algorithm is relatively

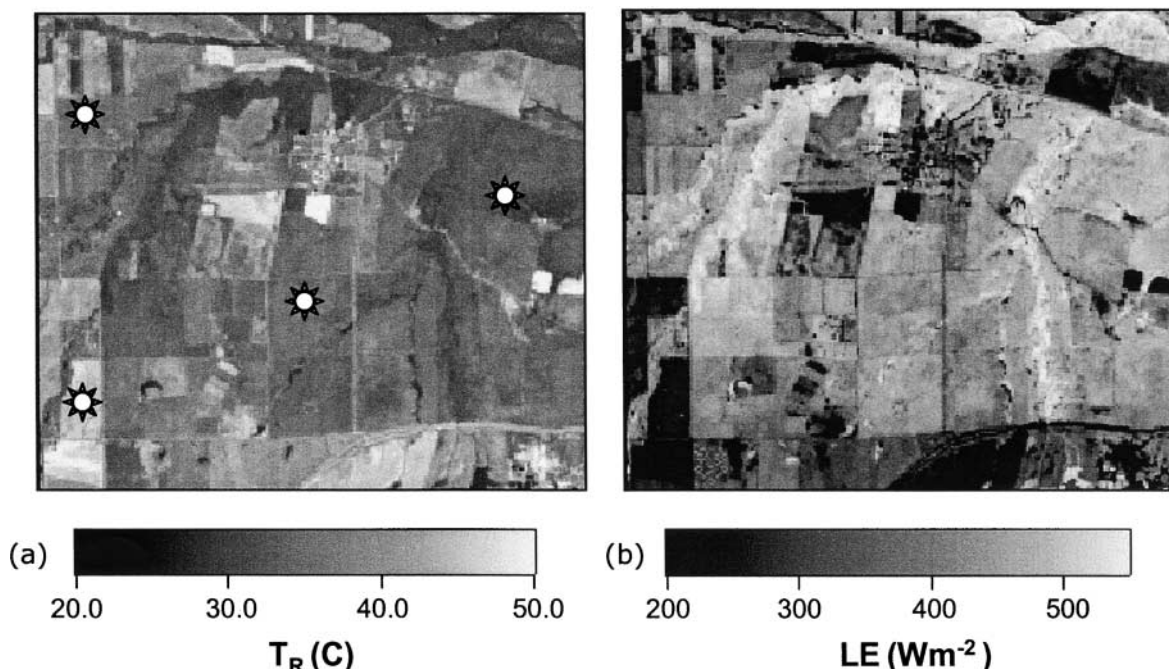


Fig. 6. Maps at 24-m resolution of (a) surface radiometric temperature (T_R) and (b) disaggregated latent heat flux estimates (LE) over an experimental study area near El Reno, OK, for 2 July 1997 (Norman et al., 2003). Stars on the radiometric temperature map indicate the locations where the measurements shown in Fig. 7 were acquired.

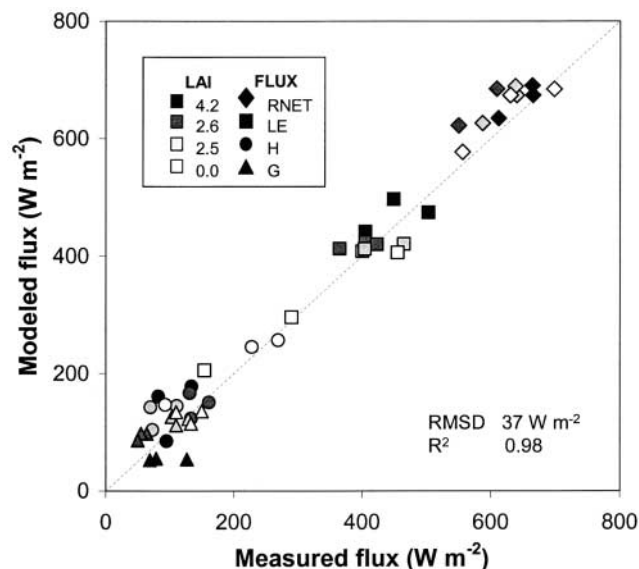


Fig. 7. Comparison of instantaneous measurements (1.5 h before local noon) of net radiation (RN), soil heat flux (G), sensible heat (H), and latent heat (LE) made in four sites of varying leaf area index (LAI) with 30-m flux estimates disaggregated using the DisALEXI technique. The root mean square difference (RMSD) between measurements and model estimates for all flux components is 38 W m^{-2} (12% of the mean observed flux), with a coefficient of determination (R^2) of 0.98 (Norman et al., 2003).

simple and computationally undemanding and is therefore well suited for operational applications such as site-specific agricultural and water resource management. From a research standpoint, however, it does not fully capture all of the important feedbacks coupling the land and atmosphere. In reality, turbulence generated over the hot, bare soil regions in Fig. 6 may be having some impact on fluxes from adjacent vegetated fields, but in DisALEXI, the fluxes from these patches are horizontally decoupled.

Large-Eddy Simulation

This question of turbulent coupling between adjacent heterogeneous patches in a landscape is a current topic of investigation in large-eddy simulation (LES) studies. The goal in LES is to resolve the large, kilometer-scale eddies, which carry 80 to 90% of the energy in the convective boundary layer, while parameterizing the effects of smaller subgrid-scale eddies, which act mainly to dissipate turbulent energy. Large-eddy simulations are run on a three-dimensional grid, typically with a horizontal resolution of 100 m and a vertical extent exceeding the scale height of the ABL, about 2 km. Mason (1994) provides a review of the LES modeling technique.

To date, most large-eddy simulations have been conducted with fixed flux boundary conditions, often prescribed in artificial patterns over the land surface to study atmospheric response to forcings of well-defined scale and strength. Avissar and Schmidt (1998), for example, studied effects of surface flux patchiness on the ABL by imposing sinusoidally varying bands of sensible and latent heating at the lower face of the LES model

grid. They found that as long as the characteristic length scale of surface heterogeneity was smaller than 5 to 10 km, and the topographical features were smaller than about 200 m, there was no significant impact on the mean characteristics of the convective boundary layer. These findings lend support to the tile disaggregation technique used in DisALEXI, which assumes uniform atmospheric conditions on the 5- to 10-km scale and that horizontal fluxes between tiles are small compared with vertical fluxes.

The prescription of surface flux boundary conditions in large-eddy simulations, however, short-circuits part of the full feedback loop that exists in nature between the land and atmosphere. The fixed fluxes cannot respond to any heterogeneity that may be transmitted into the ABL from the surface.

In a new study by Albertson et al. (2001b), surface fluxes forcing an LES model were computed internally by coupling the LES model with the two-source model (TSM-LES). Microwave, thermal, and normalized difference vegetation index (NDVI) images collected during the Monsoon '90 field experiment (Kustas and Goodrich, 1994) in Arizona were used to simulate field conditions with realistic spatial structure, providing surface boundary conditions in soil moisture, surface temperature, and vegetation cover for the two-source model. The use of state boundaries, rather than flux boundaries, allows the surface fluxes to adjust to local air properties that are influenced by upwind patches.

Albertson et al. (2001b) examined the statistical properties of modeled spatial variability in air temperature and found that variability decayed logarithmically with height above the surface. This type of analysis provides guidance for assessing errors in tile methodologies, such as used in DisALEXI, where conditions at height are held constant over a patch of landscape. They also found that the decay is more rapid for variability at smaller spatial scales. Larger structures in surface temperature are transmitted more effectively into the atmosphere, indicating enhanced coupling at surface length scales greater than 500 to 1000 m.

In another study, Kustas and Albertson (2003) compared TSM-LES-derived flux fields with fluxes generated with the two-source surface model applied as in DisALEXI, holding atmospheric conditions at 10 m above ground level fixed at regionally averaged values obtained from the LES. The variance in the remotely sensed surface temperature field was increased by two ($2\times$) and three ($3\times$) times that in the original field to evaluate the effect of the increased surface temperature contrast on surface-atmosphere coupling. The prescription of uniform atmospheric properties as an upper boundary condition resulted in significant differences in partitioning of available energy between latent and sensible heat fluxes (expressed in terms of the Bowen ratio, β) for the hotter, drier areas in the modeling domain, particularly for the $3\times$ case (Fig. 8). In the TSM-LES, local air temperature and humidity adapted to the enhancements in surface temperature, thereby dampening the response of surface fluxes to variability in surface conditions. Through such comparisons, it may

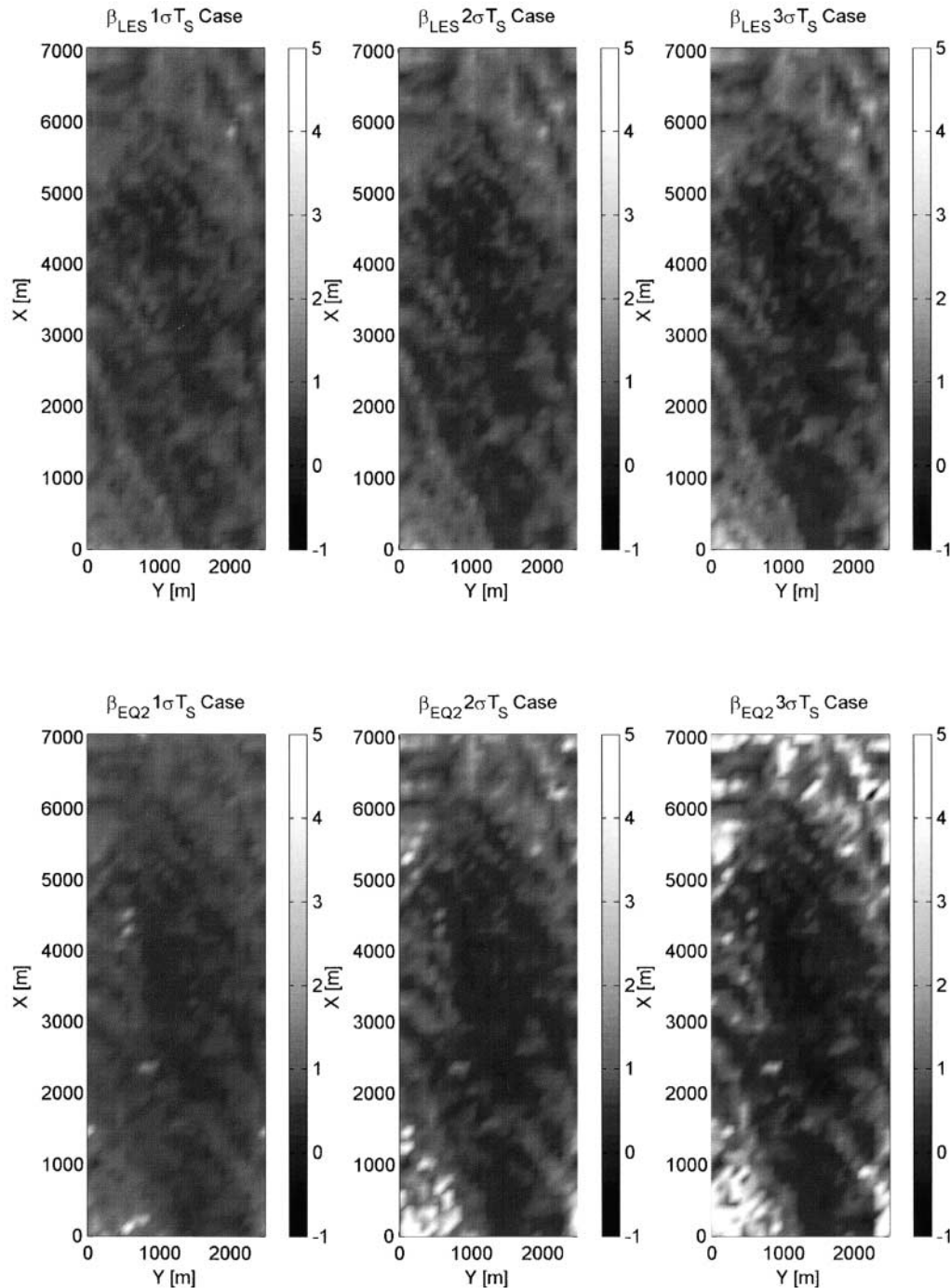


Fig. 8. Spatial fields of Bowen ratio values computed by the TSM-LES (β_{LES}) and the TSM with uniform upper boundary conditions at 10 m (β_{EQ2}) for three cases where the variance (σ) in the input surface temperature field was unchanged ($1\times$) and increased by $2\times$ and $3\times$.

be possible to derive scale- or case-dependent correction factors that could be applied to operational methodologies such as DisALEXI.

This coupling of LES with land surface modeling, using realistic state boundary conditions derived from remote sensing, is a new and exciting development that has been made possible by recent advances in computing power and parallel processing techniques. Output from models like the TSM-LES can be compared directly with lidar observations of the atmospheric turbulence

spectrum (e.g., Avissar et al., 1998), providing further insight into how land surface heterogeneities are expressed in the atmosphere.

Mesoscale—ALEX

The prognostic version of ALEX has been embedded within the Cooperative Institute for Meteorological Satellite Studies (CIMSS) Regional Assimilation System (CRAS) for purposes of improving the model land surface representation (Diak et al., 1998). CRAS assimi-

lates radiosonde and surface synoptic data at 1200 h UTC, along with satellite-derived cloud data, into a regional forecast run at 40- to 80-km spatial resolution and 48 h duration (Leslie et al., 1985; Diak, 1987; Diak et al., 1992; Wu et al., 1995).

The CRAS model has become integral to several operational applications of the ALEX model suite. The forecast component of CRAS provides prognostic boundary conditions in air temperature, wind speed, and vapor pressure for cranberry frost forecast and potato late blight severity models based on ALEX, run daily in several growing regions in Wisconsin (Diak et al., 1998; Anderson et al., 2001). The analysis component creates initialization fields for CRAS, analyzing synoptic surface and radiosonde observations onto a three-dimensional grid in a manner consistent with the model physics. Gridded fields of surface wind and atmospheric temperature profile from the CRAS analysis are input into daily regional ALEXI model runs (Mecikalski et al., 1999). The compatibility between the CRAS and ALEX/ALEXI models for such integrated applications is enhanced by the common two-source model of surface exchange embedded in each.

Model Limitations

While the models described here have utility in describing current surface conditions, they are generally not well suited for long-term predictive studies, such as simulating climate response to elevated levels of CO₂. The LUE relationships intrinsic to ALEX are based in part on empirical observations of plant physiological response under current ambient CO₂ conditions; application under altered conditions would require a close examination of environmental feedback on canopy LUE. Climate change prediction is an example where more complex land surface models, incorporating detailed plant physiological response functions, may be necessary.

Surface flux models dependent on satellite remote sensing data are also subject to stringent temporal limitations. Data are available only at satellite overpass times (often once daily or biweekly) and then only when

the scene is sufficiently clear of clouds. This suggests that a symbiosis with a more time-continuous model may be beneficial, with the remote sensing model providing updates of critical parameters that are difficult to model physically (such as soil moisture) whenever the remote sensing data are available. As such, the models described here should be useful for applications in relatively short time-scale applications, such as numerical weather prediction, crop yield forecasting, and modeling transient hydrologic phenomena.

At present, the ALEXI and DisALEXI models do not consider the effects of surface topography, for example, the effects of local slope and aspect on surface radiation receipt (e.g., Dozier and Frew, 1990; Dubayah, 1992). Topographic corrections implemented in the Cupid model will be adapted for the two-source model structure in the near future.

CONCLUSIONS

In summary, the strength of the ALEX model, the core of the suite of models described here, is that it is simple yet fairly robust, it requires only a few empirical and tunable parameters, and it can be easily inverted and coupled with other models, providing means for assimilating remote sensing data at various spatial scales. Because of its flexibility, this core land surface representation provides synergy among a suite of models covering a wide range in complexity and spatial scale (Fig. 1): the forward ALEX model for local forecasting, DisALEXI for field-scale applications, the TSM-LES model for studying turbulence-scale feedback, ALEXI for estimating regional-scale fluxes, and a mesoscale version for providing regional forecasts and analyzing synoptic weather data for use in smaller-scale applications.

The modeling framework outlined in Fig. 1 has the potential of addressing the impact of variability in soil and vegetation conditions on land-atmosphere feedback, focusing on two important characteristics of surface heterogeneity. One is related to the amplitude or severity in contrast across a landscape as investigated by Kustas and Albertson. (2003). The other is the areal extent within a model grid or pixel that is comprised of different land cover conditions (e.g., Kustas and Norman, 2000a). Both aspects of heterogeneity can be studied from a bottom-up or upscaling perspective where the consistency in the heat flux output from DisALEXI-TSM-LES and ALEXI is used as a means for assessing implicit/explicit upscaling assumptions. From a top-down or disaggregation perspective, the spatially distributed high-resolution fluxes derived from DisALEXI and TSM-LES can be contrasted to evaluate the importance of the land surface-atmosphere feedbacks. Coordinated field studies such as the 2002 Soil Moisture-Atmospheric Coupling Experiment (SMACEX; Kustas et al., 2003) provide data for model validation at multiple scales and heights (e.g., Anderson et al., 2003): tower and aircraft fluxes, atmospheric soundings, volume-imaging lidar, and aircraft and satellite remote sensing

Table 2. Scaling issues and applications for coupled land-atmosphere models.

Scale	Models	Issues	Applications
Canopy	Land surface model (LSM) (local scale)	Parameterize canopy scale feedback	Local crop yield and disease modeling
Landscape	Disaggregation (10- to 100-m resolution)	Rules for aggregated parameter formation	Field/watershed scale management
	3D LSM-LES† (100 m)	Parameterize turbulent scale dynamics and feedbacks	Research
	1D LSM-ABL‡ (5–10 km)		Regional flux mapping, climatology
Mesoscale+	LSM-mesoscale (10–50 km)	Parameterize mesoscale circulations and feedbacks	Mesoscale forecasting
	LSM-general circulation model (100 km)	Examine global scale circulations and feedbacks	Climate and land use change simulation

† LES, large-eddy simulation.

‡ ABL, atmospheric boundary layer.

imagery (Eichinger et al., 2003; Prueger et al., 2003; MacPherson et al., 2003).

In more general terms, a process has evolved over time by which we are slowly filling gaps in our understanding of how upscaling and downscaling can be accomplished (Table 2): We build complex models of land-atmosphere interaction at small scales, extract the essence of this small-scale behavior in the form of parameterizations, and incorporate these parameterizations into models on the next larger scale. Similarly, larger-scale models reveal valuable information about the faulty assumptions we might be making at smaller scales by neglecting important feedbacks.

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REFERENCES

- Albertson, J.D., G.G. Katul, and P. Wiberg. 2001a. Relative importance of local and regional controls on coupled water, carbon, and energy fluxes. *Adv. Water Resour.* 24:1103-1118.
- Albertson, J.D., W.P. Kustas, and T.M. Scanlon. 2001b. Large-eddy simulation over heterogeneous terrain with remotely sensed land surface conditions. *Water Resour. Res.* 37:1939-1953.
- Anderson, M.C., W.L. Bland, J.M. Norman, and G.R. Diak. 2001. Canopy wetness and humidity prediction using satellite and synoptic-scale meteorological observations. *Plant Dis.* 85:1018-1026.
- Anderson, M.C., J.M. Norman, G.R. Diak, W.P. Kustas, and J.R. Mecikalski. 1997. A two-source time-integrated model for estimating surface fluxes using thermal infrared remote sensing. *Remote Sens. Environ.* 60:195-216.
- Anderson, M.C., J.M. Norman, W.P. Kustas, J.H. Prueger, C.M.U. Neale, J.I. MacPherson, J.R. Mecikalski, and G.R. Diak. 2003. Comparison of aircraft- and tower-measured fluxes acquired during SMACEX with predictions from a regional atmosphere-land exchange model. *In Proc. Conf. on Hydrology, 17th, Long Beach, CA [CD-ROM]*. 9-13 Feb. 2003. Am. Meteorological Soc., Boston.
- Anderson, M.C., J.M. Norman, T.P. Meyers, and G.R. Diak. 2000. An analytical model for estimating canopy transpiration and carbon assimilation fluxes based on canopy light-use efficiency. *Agric. For. Meteorol.* 101:265-289.
- Anthes, R.A. 1984. Enhancement of convective precipitation by mesoscale variations in vegetative covering in semiarid regions. *J. Clim. Appl. Meteorol.* 23:541-554.
- Arkebauer, T.J., A. Weiss, T.R. Sinclair, and A. Blum. 1994. In defense of radiation use efficiency: A response to Demetriades-Shah. *Agric. For. Meteorol.* 68:221-227.
- Avissar, R. 1992. Conceptual aspects of a statistical-dynamical approach to represent landscape subgrid-scale heterogeneities in atmospheric models. *J. Geophys. Res.* 97:2729-2742.
- Avissar, R. 1993. Observations of leaf stomatal conductance at the canopy scale: An atmospheric modeling perspective. *Boundary-Layer Meteorol.* 64:127-148.
- Avissar, R. 1998. Which type of soil-vegetation-atmosphere transfer scheme is needed for general circulation models: A proposal for a higher-order scheme. *J. Hydrol. (Amsterdam)* 212-213:136-154.
- Avissar, R., E.W. Eloranta, K. Güler, and G.J. Tripoli. 1998. An evaluation of the large-eddy simulation option of the Regional Atmospheric Modeling System in simulating a convective boundary layer: A FIFE case study. *J. Atmos. Sci.* 55:1109-1130.
- Avissar, R., and Y. Liu. 1996. Sensitivity of shallow convective precipitation induced by land surface heterogeneities to dynamical and cloud microphysical parameters. *J. Geophys. Res.* 101:7477-7497.
- Avissar, R., and R.A. Pielke. 1989. A parameterization of heterogeneous land surface for atmospheric numerical models and its impact on regional meteorology. *Mon. Weather Rev.* 117:2113-2136.
- Avissar, R., and T. Schmidt. 1998. An evaluation of the scale at which ground-surface heat flux patchiness affects the convective boundary layer using large-eddy simulations. *J. Atmos. Sci.* 55:2666-2689.
- Ball, J.T., I.E. Woodrow, and J.A. Berry. 1986. A model predicting stomatal conductance and its contribution to the control of photosynthesis under different environmental conditions. p. 221-225. *In J. Biggins (ed.) Progress in photosynthesis research*. Nijhoff, Dordrecht, the Netherlands.
- Bastiaansen, W.G.M., M. Menenti, R.A. Feddes, and A.A.M. Holtslag. 1998. A remote sensing surface energy balance algorithm for land (SEBAL). *J. Hydrol. (Amsterdam)* 212-213:198-212.
- Bonan, G.B., D. Pollard, and S.L. Thompson. 1993. Influence of sub-grid-scale heterogeneity in leaf area index, stomatal resistance, and soil moisture on grid-scale land-atmosphere interactions. *J. Clim.* 6:1882-1897.
- Boni, G., D. Entekhabi, and F. Castelli. 2001. Land data assimilation with satellite measurements for the estimation of surface energy balance components and surface control on evaporation. *Water Resour. Res.* 37:1713-1722.
- Brutsaert, W. 1984. *Evaporation into the atmosphere: Theory, history and applications*. D. Reidel, Boston.
- Bunce, J.A., K.B. Wilson, and T.N. Carlson. 1997. The effect of doubled CO₂ on water use by alfalfa and orchard grass: Simulating evapotranspiration using canopy conductance measurements. *Global Change Biol.* 3:81-87.
- Campbell, G.S., and J.M. Norman. 1998. *An introduction to environmental biophysics*. Springer-Verlag, New York.
- Carlson, T.N., and J.A. Bunce. 1996. Will a doubling of atmospheric carbon dioxide concentration lead to an increase or decrease in water consumption by crops? *Ecol. Modell.* 88:241-246.
- Chebouni, A., E.G. Njoku, J.-P. Lhomme, and Y.H. Kerr. 1995. Approaches for averaging surface parameters and fluxes over heterogeneous terrain. *J. Clim.* 8:1386-1393.
- Chebouni, A., C. Watts, Y.H. Kerr, G. Dedieu, J.-C. Rodriguez, F. Santiago, P. Cayrol, G. Boulet, D.C. Goodrich. 2000. Methods to aggregate turbulent fluxes over heterogeneous surfaces: Application to SALSA data set in Mexico. *Agric. For. Meteorol.* 105:133-144.
- Chen, F., and R. Avissar. 1994. Impact of land-surface moisture variability on local shallow convective cumulus and precipitation in large-scale models. *J. Appl. Meteorol.* 33:1382-1401.
- Collatz, G.J., J.T. Ball, C. Grivet, and J.A. Berry. 1991. Physiological and environmental regulation of stomatal conductance, photosynthesis and transpiration: A model that includes a laminar boundary layer. *Agric. For. Meteorol.* 54:107-136.
- Collatz, G.J., J. Ribas-Carbo, and J.A. Berry. 1992. Coupled photosynthesis-stomatal conductance model for leaves of C4 plants. *Aust. J. Plant Physiol.* 19:519-538.
- Daughtry, C.S.T., K.P. Gallow, and M.E. Bauer. 1983. Spectral estimates of solar radiation intercepted by corn canopies. *Agron. J.* 75:527-531.
- Diak, G.R. 1987. Assimilation of scalar versus horizontal gradient information from the VAS into a mesoscale model. *J. Clim. Appl. Meteor.* 26:738-748.
- Diak, G.R., M.C. Anderson, W.L. Bland, J.M. Norman, J.M. Mecikalski, and R.M. Aune. 1998. Agricultural management decision aids driven by real-time satellite data. *Bull. Am. Meteorol. Soc.* 79:1345-1355.
- Diak, G.R., D. Kim, M.S. Whipple, and X. Wu. 1992. Preparing for the AMSU. *Bull. Am. Meteorol. Soc.* 73:1971-1984.
- Divakarla, M.G. 1997. Estimating spatially distributed surface fluxes from satellite data, in-situ measurements and the Cupid model using GIS. Ph.D. thesis. Univ. of Wisconsin, Madison.
- Dozier, J., and J. Frew. 1990. Rapid calculation of terrain parameters for radiation modeling from digital elevation data. *IEEE Trans. Geosci. Remote Sens.* 28:963-969.
- Dubayah, R. 1992. Estimating net solar-radiation using Landsat Thematic Mapper and digital elevation data. *Water Resour. Res.* 28:2469-2484.
- Eichinger, W.E., D.I. Cooper, L.E. Hipps, W.P. Kustas, C.M.U. Neale, and J.H. Prueger. 2003. High resolution lidar evaporative fluxes over corn and soybean crops in central Iowa during SMACEX. *In Proc. Conf. on Hydrology, 17th, Long Beach, CA [CD-ROM]*. 9-13 Feb. 2003. Am. Meteorological Soc., Boston.

- Field, C.B. 1991. Ecological scaling of carbon gain to stress and resource availability. p. 35–65. *In* H.A. Mooney, W.E. Winner, and E.J. Pell (ed.) *Response of plants to multiple stresses*. Academic Press, San Diego.
- Freedman, J.M., D.R. Fitzjarrald, K.E. Moore, and R.K. Sakai. 2001. Boundary layer clouds and vegetation–atmosphere feedbacks. *J. Clim.* 14:180–197.
- French, A.N., T.J. Schmugge, and W.P. Kustas. 2000. Surface fluxes over the SGP site with remotely sensed data. *Phys. Chem. Earth, B* 25:167–172.
- Gillies, R.R., and T.N. Carlson. 1995. Thermal remote-sensing of surface soil-water content with partial vegetation cover for incorporation into climate models. *J. Appl. Meteorol.* 34:745–756.
- Goetz, S.J., and S.D. Prince. 1998. Modeling terrestrial carbon exchange and storage: The evidence for and implications of functional convergence in light use efficiency. p. 57–92. *In* A.H. Fitter and D. Raffaelli (ed.) *Advances in ecological research*. Academic Press, San Diego.
- Gottschalk, J.C., R.R. Gillies, and T.N. Carlson. 2001. The simulation of canopy transpiration under doubled CO₂: The evidence and impact of feedbacks on transpiration in two 1-D soil-vegetation-atmosphere-transfer models. *Agric. For. Meteorol.* 106:1–21.
- Gower, S.T., C.J. Kucharik, and J.M. Norman. 1999. Direct and indirect estimation of leaf area index, f_{APAR} and net primary production of terrestrial ecosystems. *Remote Sens. Environ.*
- Grantz, E.A., and F.C. Meinzer. 1990. Stomatal response to humidity in a sugarcane field: Simultaneous porometric and micrometeorological measurements. *Plant Cell Environ.* 13:27–37.
- Hall, F.G., K.F. Huemmrich, S.J. Goetz, P.J. Sellers, and J.E. Nickerson. 1992. Satellite remote sensing of surface energy balance: Success, failures and unresolved issues in FIFE. *J. Geophys. Res.* 97:19061–19089.
- Holwill, C.J., and J.B. Stewart. 1992. Spatial variability of evaporation derived from aircraft and ground-based data. *J. Geophys. Res.* 97:18673–18680.
- Horst, T.W., and J.C. Weil. 1992. Footprint estimation for scalar flux measurements in the atmospheric surface layer. *Boundary-Layer Meteorol.* 59:279–296.
- Jackson, T.J., D.M. Le Vine, A.Y. Hsu, A. Oldak, P.J. Starks, C.T. Swift, J.D. Isham, and M. Haken. 1999. Soil moisture mapping at regional scales using microwave radiometry: The Southern Great Plains hydrology experiment. *IEEE Trans. Geosci. Remote Sens.* 37:2136–2151.
- Jacobs, C.M.J., and H.A.R. DeBruin. 1992. The sensitivity of regional transpiration to land-surface characteristics: Significance of feedback. *J. Clim.* 5:683–698.
- Jacobs, C.M.J., and H.A.R. DeBruin. 1997. Predicting regional transpiration at elevated atmospheric CO₂: Influence of the PBL–vegetation interaction. *J. Appl. Meteorol.* 36:1663–1675.
- Jarvis, P.G. 1993. Prospects for bottom-up models. p. 115–126. *In* J.R. Ehleringer and C.B. Field (ed.) *Scaling physiological processes leaf to globe*. Academic Press, San Diego.
- Jarvis, P.G. 1995. Scaling processes and problems. *Plant Cell Environ.* 18:1079–1089.
- Jarvis, P.G., and K.G. McNaughton. 1986. Stomatal control of transpiration: Scaling up from leaf to region. *Adv. Ecol. Res.* 15:1–49.
- Jones, H.G. 1998. Stomatal control of photosynthesis and transpiration. *J. Exp. Bot.* 49:387–398.
- Klaassen, W. 1992. Average fluxes from heterogeneous vegetated regions. *Boundary-Layer Meteorol.* 58:329–354.
- Kubota, A., and M. Sugita. 1994. Radiometrically determined skin temperature and scalar roughness to estimate surface heat flux: I. Parameterization of radiometric scalar roughness. *Boundary-Layer Meteorol.* 69:394–416.
- Kumar, M., and J.L. Monteith. 1981. Remote sensing of plant growth. p. 347–364. *In* P.A. Huxley (ed.) *Plants and the daylight spectrum*. Int. Council for Res. in Agroforestry, Nairobi, Kenya.
- Kustas, W.P., and J.D. Albertson. 2003. Effects of surface temperature contrast on land–atmosphere exchange: A case study from Monsoon 90. *Water Resour. Res.* doi 10.1029/2001WR001226.
- Kustas, W.P., B.J. Choudhury, M.S. Moran, R.D. Reginato, R.D. Jackson, L.W. Gay, and H.L. Weaver. 1989. Determination of sensible heat flux over sparse canopy using thermal infrared data. *Agric. For. Meteorol.* 44:197–216.
- Kustas, W.P., and D.C. Goodrich. 1994. Preface, MONSOON '90 Multidisciplinary Experiment. *Water Resour. Res.* 30:1211–1225.
- Kustas, W.P., and J.M. Norman. 1999a. Evaluation of soil and vegetation heat flux predictions using a simple two-source model with radiometric temperatures for partial canopy cover. *Agric. For. Meteorol.* 94:13–25.
- Kustas, W.P., and J.M. Norman. 1999b. Reply to comments about the basic equations of dual-source vegetation–atmosphere transfer models. *Agric. For. Meteorol.* 94:275–278.
- Kustas, W.P., and J.M. Norman. 2000a. Evaluating the effects of subpixel heterogeneity on pixel average fluxes. *Remote Sens. Environ.* 74:327–342.
- Kustas, W.P., and J.M. Norman. 2000b. A two-source energy balance approach using directional radiometric temperature observations for sparse canopy covered surfaces. *Agron. J.* 92:847–854.
- Kustas, W.P., J.H. Prueger, J.L. Hatfield, J.I. MacPherson, M. Wolde, C.M.U. Neale, W.E. Eichinger, D.I. Cooper, J.M. Norman, and M.C. Anderson. 2003. An overview of the Soil-Moisture-Atmospheric-Coupling Experiment (SMACEX) in central Iowa. *In* Proc. Conf. on Hydrology, 17th, Long Beach, CA [CD-ROM]. 9–13 Feb. 2003. Am. Meteorological Soc., Boston.
- Kustas, W.P., X. Zhan, and T.J. Schmugge. 1998. Combining optical and microwave remote sensing for mapping energy fluxes in a semiarid watershed. *Remote Sens. Environ.* 64:116–131.
- Landsberg, J.J., S.D. Prince, P.G. Jarvis, R.E. McMurtrie, R. Luxmore, and B.E. Medlyn. 1997. Energy conversion and use in forests: The analysis of forest production in terms of radiation utilisation efficiency (e). p. 273–298. *In* H.L. Gholz, K. Nakane, and H. Shimoda (ed.) *Use of remote sensing in the modeling of forest productivity*. Kluwer Academic Publ., New York.
- Leslie, L.M., G.A. Mills, L.W. Logan, D.J. Gauntlett, G.A. Kelly, J.L. McGregor, and M.J. Manton. 1985. A high resolution primitive equations model for operations and research. *Aust. Meteorol. Mag.* 33:11–36.
- Lhomme, J.-P. 1992. Energy balance of heterogeneous terrain: Averaging the controlling parameters. *Agric. For. Meteorol.* 61:11–21.
- Lhomme, J.-P., A. Chehbouni, and B. Monteny. 1994. Effective parameters of surface energy balance in heterogeneous landscape. *Boundary-Layer Meteorol.* 71:297–309.
- Li, B., and R. Avissar. 1994. The impact of spatial variability of land-surface characteristics on land-surface heat fluxes. *J. Clim.* 7: 527–537.
- Li, J., and S. Islam. 1999. On the estimation of soil moisture profile and surface fluxes partitioning from sequential assimilation of surface layer soil moisture. *J. Hydrol. (Amsterdam)* 220:86–103.
- MacPherson, J.I., M. Wolde, W.P. Kustas, and J.H. Prueger. 2003. Aircraft and tower-measured fluxes over rapidly growing corn and soybean crops in central Iowa. *In* Proc. Conf. on Hydrology, 17th, Long Beach, CA [CD-ROM]. 9–13 Feb. 2003. Am. Meteorological Soc., Boston.
- Magnani, F., S. Leonardi, R. Tognetti, J. Grace, and M. Borghetti. 1998. Modelling the surface conductance of a broad-leaf canopy: Effects of partial decoupling from the atmosphere. *Plant Cell Environ.* 21:867–879.
- Mahfouf, J.F., E. Richard, and P. Mascart. 1987. The influence of soil and vegetation in the development of mesoscale circulations. *J. Clim. Appl. Meteorol.* 26:1483–1495.
- Mason, P.J. 1994. Large-eddy simulation: A critical review of the technique. *Q. J. R. Meteorol. Soc.* 120:1–26.
- McNaughton, K.G. 1994. Effective stomatal and boundary-layer resistances of heterogeneous surfaces. *Plant Cell Environ.* 17:1061–1068.
- McNaughton, K.G., and P.G. Jarvis. 1991. Effects of spatial scale on stomatal control of transpiration. *Agric. For. Meteorol.* 54:269–301.
- McNaughton, K.G., and T.W. Spriggs. 1986. A mixed-layer model for regional evaporation. *Boundary-Layer Meteorol.* 74:262–288.
- Mecikalski, J.M., G.R. Diak, M.C. Anderson, and J.M. Norman. 1999. Estimating fluxes on continental scales using remotely-sensed data in an atmosphere–land exchange model. *J. Appl. Meteorol.* 38: 1352–1369.
- Monteith, J.L. 1977. Climate and the efficiency of crop production in Britain. *Philos. Trans. R. Soc. London, Ser. B* 281:277–294.
- Moran, M.S. 2003. Thermal infrared measurement as an indicator of plant ecosystem health. *In* D.A. Quattrochi and J. Luvall (ed.)

- Thermal remote sensing in land surface processes (in press). Taylor and Francis, London.
- Moran, M.S., T.R. Clarke, Y. Inoue, and A. Vidal. 1994. Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sens. Environ.* 49: 246–263.
- Myneni, R.B., F.G. Hall, P.J. Sellers, and A.L. Marshak. 1995a. The interpretation of spectral vegetation indices. *IEEE Trans. Geosci. Remote Sens.* 33:481–486.
- Myneni, R.B., S. Maggion, J. Jaquinta, J.L. Privette, N. Gobron, B. Pinty, D.S. Kimes, M.M. Verstraete, and D.L. Williams. 1995b. Optical remote sensing of vegetation: Modeling, caveats, and algorithms. *Remote Sens. Environ.* 51:169–188.
- Norman, J.M. 1979. Modeling the complete crop canopy. p. 249–277. *In* B.J. Barfield and J.F. Gerber (ed.) *Modification of the aerial environment of plants*. ASAE, St. Joseph, MI.
- Norman, J.M., M.C. Anderson, W.P. Kustas, A.N. French, J.R. Mecikalski, R.D. Torn, G.R. Diak, T.J. Schmugge, and B.C.W. Tanner. 2003. Remote sensing of surface energy fluxes at 10^1 -m pixel resolutions. *Water Resour. Res.* doi: 10.1029/2002WRR001775.
- Norman, J.M., and T.J. Arkebauer. 1991. Predicting canopy light-use efficiency from leaf characteristics. p. 125–143. *In* J.T. Ritchie and R.J. Hanks (ed.) *Modeling plant and soil systems*. Agron. Monogr. 31. ASA, CSSA, and SSSA, Madison, WI.
- Norman, J.M., and G. Campbell. 1983. Application of a plant-environment model to problems in irrigation. p. 156–188. *In* D. Hillel (ed.) *Advances in irrigation*. Academic Press, New York.
- Norman, J.M., M. Divakarla, and N.S. Goel. 1995a. Algorithms for extracting information from remote thermal-IR observations of the earth's surface. *Remote Sens. Environ.* 51:157–168.
- Norman, J.M., W.P. Kustas, and K.S. Humes. 1995b. A two-source approach for estimating soil and vegetation energy fluxes from observations of directional radiometric surface temperature. *Agric. For. Meteorol.* 77:263–293.
- Norman, J.M., and W.R. Polley. 1989. Canopy photosynthesis. p. 227–241. *In* W.R. Briggs (ed.) *Photosynthesis*. Alan R. Liss, New York.
- Palluconi, F.D., and G.R. Meeks. 1985. Thermal infrared multispectral scanner (TIMS): An investigator's guide to TIMS data. JPL Publ. 85–32. Jet Propulsion Lab., California Inst. of Technol., Pasadena, CA.
- Pielke, R.A., G.A. Dalu, J.S. Snook, T.J. Lee, and T.G.F. Kittel. 1991. Nonlinear influence of mesoscale land use on weather and climate. *J. Clim.* 4:1053–1069.
- Pinty, J.P., P. Mascart, E. Richard, and R. Rosset. 1989. An investigation of mesoscale flows induced by vegetation inhomogeneities using an evapotranspiration model calibrated against HAPEX-MOBILHY data. *J. Appl. Meteorol.* 28:976–992.
- Potter, C.S., J.T. Randerson, C.B. Field, P.A. Matson, P.M. Vitousek, H.A. Mooney, and S.A. Klooster. 1993. Terrestrial ecosystem production: A process model based on global satellite and surface data. *Global Biogeochem. Cycles* 7:811–841.
- Prince, S.D., and S.J. Goward. 1995. Global primary production: A remote sensing approach. *J. Biogeogr.* 22:815–835.
- Prueger, J.H., W.P. Kustas, L.E. Hipps, J.L. Hatfield, A. Cahill, C. Williams, J.I. MacPherson, M. Wolde, J. Albertson, W.E. Eichinger, D.I. Cooper, N. Brunzell, and R. Gillies. 2003. Spatial variability of turbulent fluxes across a corn/soybean production region in central Iowa. *In* Proc. Conf. on Hydrology, 17th, Long Beach, CA [CD-ROM]. 9–13 Feb. 2003. Am. Meteorological Soc., Boston.
- Raupach, M.R. 1991. Vegetation-atmosphere interaction in homogeneous and heterogeneous terrain: Some implications of mixed-layer dynamics. *Vegetatio* 91:105–120.
- Raupach, M.R. 1998. Influences of local feedbacks on land-air exchanges of energy and carbon. *Global Change Biol.* 4:477–494.
- Raupach, M.R., and J.J. Finnigan. 1995. Scale issues in boundary-layer meteorology: Surface energy balances in heterogeneous terrain. *Hydrol. Processes* 9:589–612.
- Ruimy, A., G. Dedieu, and B. Saugier. 1994. Methodology for the estimation of terrestrial net primary production from remotely sensed data. *J. Geophys. Res.* 99:5263–5283.
- Schmid, H.P. 1994. Source areas for scalars and scalar fluxes. *Boundary-Layer Meteorol.* 67:293–318.
- Schuepp, P.H., M.Y. Leclerc, J.I. MacPherson, and R.L. Desjardins. 1990. Footprint prediction of scalar fluxes from analytical solutions of the diffusion equation. *Boundary-Layer Meteorol.* 50:355–373.
- Schuepp, P.H., J.I. MacPherson, and R.L. Desjardins. 1992. Adjustment of footprint correction for airborne flux mapping over the FIFE site. *J. Geophys. Res.* 97:18455–18466.
- Segal, M., and R.W. Arritt. 1992. Nonclassical mesoscale circulations caused by surface sensible heat-flux gradients. *Bull. Am. Meteorol. Soc.* 73:1593–1604.
- Sellers, P.J., D.A. Randall, G.J. Collatz, J.A. Berry, C.B. Field, D.A. Dazlich, C. Zhang, G.D. Collelo, and L. Bounoua. 1996. A revised land surface parameterization (SiB2) for atmospheric GCMs: I. Model formulation. *J. Clim.* 9:676–705.
- Shuttleworth, W.J. 1988. Macrohydrology: The new challenge for process hydrology. *J. Hydrol. (Amsterdam)* 100:31–56.
- Steinmetz, S., M. Guerif, R. DeLecolle, and F. Baret. 1990. Spectral estimates of the photosynthetically active radiation and light-use efficiency of a winter-wheat crop subjected to nitrogen and water deficiencies. *Int. J. Remote Sens.* 11:1797–1808.
- Stewart, J.B., W.P. Kustas, K.S. Humes, W.D. Nichols, M.S. Moran, and A.A.R. DeBruin. 1994. Sensible heat flux-radiometric surface temperature relationship for eight semiarid areas. *J. Appl. Meteorol.* 33:1110–1117.
- Twine, T.E. 1998. Underestimation of eddy covariance fluxes over a grassland. M.S. thesis. Univ. of Wisconsin, Madison.
- Vining, R.C., and B.L. Blad. 1992. Estimation of sensible heat flux from remotely sensed canopy temperatures. *J. Geophys. Res.* 97:18951–18954.
- Wieringa, J. 1986. Roughness-dependent geographical interpolation of surface wind speed averages. *Q. J. R. Meteorol. Soc.* 112:867–889.
- Wilson, K.B., T.N. Carlson, and J.A. Bunce. 1999. Feedback significantly influences the simulated effect of CO₂ on seasonal evapotranspiration from two agricultural species. *Global Change Biol.* 5:903–917.
- Wu, X., G.R. Diak, C.M. Hayden, and J.A. Young. 1995. Short-range precipitation forecasts using assimilation of simulated satellite water vapor profiles and cloud liquid water. *Mon. Weather Rev.* 123:347–365.
- Wullschlegel, S.D., K.B. Wilson, and P.J. Hanson. 2000. Environmental control of whole-plant transpiration, canopy conductance and estimates of the decoupling coefficient for large red maple trees. *Agric. For. Meteorol.* 104:157–168.